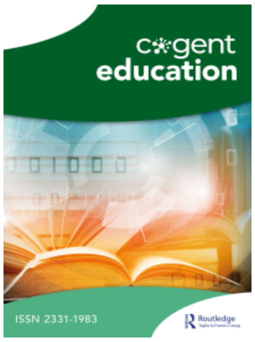
Article:

Klyshbekova, M. and Forsberg, A. (2026) ‘Learning to use AI to help us but not to do it for us’: understanding UK undergraduate students’ use of GenAI. Cogent Education, 13 (1). 2650254. ISSN: 2331-186X

https://doi.org/10.1080/2331186x.2026.2650254



Cogent Education

ISSN: 2331-186X (Online) Journal homepage: www.tandfonline.com/journals/oaed20

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COGENT EDUCATION
2026, VOL. 13, NO. 1, 2650254
https://doi.org/10.1080/2331186X.2026.2650254

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'Learning to use AI to help us but not to do it for us': understanding UK undergraduate students' use of GenAI

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ABSTRACT

This paper explores undergraduate students' views on generative artificial intelligence (GenAI) and some characteristics of students who are more likely to use GenAI. We report results from a mixed-methods study. The quantitative study explored GenAI use, 'addiction', and attitudes in a sample of 250 UK undergraduate students. We found that younger students were more likely to use GenAI for their coursework than older students, and male students reported higher degrees of GenAI familiarity than female students. Participants with higher self-esteem were more likely to report using GenAI for their assignments, and students who were more confident in their ability to achieve higher grades also reported being more familiar with GenAI. Students with higher working memory ability reported higher GenAI familiarity. The qualitative study reported students' positive views and concerns about ethics and the stigma associated with using such tools. We conclude the study with key implications, highlighting areas for consideration.

ARTICLE HISTORY
Received 3 October 2025
Revised 2 February 2026
Accepted 20 February 2026

KEYWORDS
Generative AI; UK; undergraduate students; working memory; personality; academic behavioural confidence; self-esteem

SUBJECTS
Social Sciences; Behavioral Sciences; Behavioral Neuroscience; Cognitive Neuroscience; Cognitive Neuroscience of Language; Social Sciences; Behavioral Sciences; Developmental Psychology; Language Development; Social Sciences; Behavioral Sciences; Developmental Psychology; Infancy

1. Introduction

In November 2022, the public release of generative AI tools such as ChatGPT marked a crucial turning point across various sectors, including higher education. For many, these tools sparked curiosity and enthusiasm because of their 'magic-wand-like' features that allow one to instantly generate text, summaries, and examples based on simple prompts (Klyshbekova & Abbott, 2024). At the same time, their sudden availability also raised widespread concern, especially within universities. Educators, universities, and policymakers expressed anxiety and concern that unrestricted access to ChatGPT and other similar tools could threaten academic integrity by allowing new types of cheating and outsourcing of assessed works (Giannakos et al., 2025; Mintz et al., 2023). Consequently, the arrival of GenAI in higher education has been influenced by differing interpretations of its role and purpose, fluctuating between enthusiasm for its capabilities and worries about its potential to disrupt the system.

Amidst university concern and technological optimism, there has been significant growth in research exploring the tools' capabilities, limitations, and strategies for their use (Al Shloul et al., 2024; Cotton et al., 2024; Giannakos et al., 2025; Kasneci et al., 2023). In particular, much of the early literature has

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focused on *what these tools can do*, identifying frameworks that seek to delineate acceptable from unacceptable uses of AI (see for example, Davis, 2024). Although this body of work has provided valuable insights, it has often approached GenAI from an institutional or instructional lens, leaving students' perspectives out of the frame.

What remains relatively underexplored are the *characteristics of students who are more likely to utilise GenAI*, how students perceive these tools, and how these perceptions influence their experiences with them. University students are a diverse group with varied backgrounds and experiences, and their use of GenAI is likely to be different based on a variety of characteristics, as well as individual learning experiences and needs. Moreover, understanding the motivations and underlying reasons for GenAI use is crucial for formulating evidence-based responses to its integration within higher education.

Thus, in this mixed-methods study, we aimed to illuminate the characteristics of students who are more likely to utilise GenAI as well as the underlying factors that shape students' motivations to use these tools. Specifically, this research explored the following two central research questions:

- RQ1.0: What student characteristics are associated with the use of GenAI tools among UK university students?
- RQ2.0: How do UK university students perceive and experience the use of GenAI tools for learning, including their motivations and the meanings they attribute to these tools?

Using a quantitative approach, we first examined some of the characteristics of students more likely to use GenAI, including factors like gender, age, first language, personality traits, self-esteem, academic confidence, and working memory ability. We then used a qualitative approach to explore UK university students' views on their experience using GenAI, including their motivations to use such tools and what GenAI means to them.

The rest of this article is organised as follows. We begin with a review of the existing literature on GenAI in higher education, focusing on aspects such as demographic factors, self-esteem, academic behavioural confidence, cognitive ability, and working memory. Next, we describe the study's methodology, including the mixed-methods approach, participants, data collection, and analysis procedures. The following section presents the findings from both quantitative and qualitative data. The article concludes with a discussion of the results, limitations, implications for higher education, and directions for future research.

2. Literature review

Biggs (2011) asserts that students' views of their learning environment, abilities, and teaching methods greatly influence how they learn and their outcomes. Favourable perceptions tend to foster a deep learning approach, whereas unfavourable perceptions often lead to a surface approach. Consequently, understanding student perceptions is vital when considering GenAI tools. The 3 P model by Biggs (2011) identifies three key factors affecting learning results: student-related factors, teaching-related factors, and the system's overall interactive effects. Understanding students' views in this system is crucial for interpreting how GenAI is incorporated into learning practices and its possible influence on education.

2.1. GenAI in education

GenAI is a technology that uses deep learning models to produce content based on prompts (Lim et al., 2023, p. 2). It represents a form of AI that gained widespread attention with the emergence of ChatGPT. Although GenAI is a relatively recent phenomenon, researchers have been exploring AI's role in education for years, focusing on adaptive teaching, personalised learning, and the integration of AI technologies into classrooms (Farinosi & Melchior, 2025).

In the realm of education, GenAI and ChatGPT have become central topics of intense debate, with many weighing their potential benefits against associated risks (Kasneci et al., 2023). Some educators see these tools as highly beneficial and actively integrate them into their teaching and learning approaches. Others, however, consider them a possible threat to the education system. The research in this area is still evolving, with ongoing discussions often highlighting the challenges and difficulties faced by educators and institutions (Terwiesch, 2023) or the potential advantages these tools offer to students (Shen et al., 2023).

The discussion regarding the use of GenAI pertains to its potential to influence and transform students' learning experiences (Damaševičius & Sidekerskiene, 2024). Lai et al. (2023) reported that students can utilise ChatGPT to generate responses to their inquiries, receive personalised academic support, and obtain feedback.

Conversely, some stakeholders perceive GenAI as a tool that could potentially undermine the integrity of education (Lim et al., 2023). Undoubtedly, one of the primary concerns expressed is GenAI's capacity to produce text-based outputs on any given subject. This raises issues such as the originality of work, as the widespread accessibility of the tool may lead to an increase in instances of plagiarism. To address the challenge of cheating facilitated by GenAI, many universities have adopted a restrictive stance by prohibiting the use of these tools (Castillo, 2023), while others are proactively establishing guidelines for the responsible use of GenAI technologies (Dai et al., 2025).

As the potential benefits and risks of incorporating GenAI in educational practice are being discussed, it is also essential to consider the impact of GenAI use on equality in education. Farrelly and Baker (2023) suggested that actual and perceived cognitive ability is a crucial determinant of social outcomes in modern information economies and that GenAI may disrupt or equalise the distribution of this ability. Indeed, GenAI may allow more equitable access to learning, including support for students with learning disabilities (Bhatti et al., 2024). More broadly, if GenAI is helpful for educational outcomes, students who are less likely to use it may be disadvantaged. Alternatively, if GenAI reliance hinders learning, students who are more likely to use it (e.g. due to a lack of confidence in their academic ability) may be especially vulnerable. Recent research has highlighted differences in the use of GenAI based on factors like gender (Strzelecki & ElArabawy, 2024), age (Cho & Ofosu-Anim, 2025), and personality traits (Kaya et al., 2024). Thus, our study aimed to better understand some of the characteristics of students who are more likely to use GenAI as well as their experiences of using such tools.

2.2. Demographic characteristics (age, gender, and first-language)

Previous research found that younger students were more likely to use and hold more positive attitudes toward AI tools (Hernandez-de-Menendez et al., 2020). Some studies suggested that male students were more likely to engage with AI tools than female students (Strzelecki & ElArabawy, 2024) and that men appear to have more favourable attitudes toward AI than women (Zhang & Dafoe, 2019). Aldasoro et al. (2025) found that 50% of men versus 37% of women had used GenAI in the last 12 months, a gap that appeared partly explained by privacy concerns and trust. In contrast, in a sample of students and non-students aged between 18 and 51 years, Kaya et al. (2024) found that gender did not significantly predict attitudes toward AI. Moreover, Klarin et al. (2024) observed no gender differences in the frequency of use and perceived usefulness of GenAI for schoolwork in a sample of adolescents. Finally, non-native English speakers studying in an English-speaking institution reported more frequent use of ChatGPT for writing (Baek et al., 2024). In a sample of non-native English-speaking students, the use of the GenAI 'Grammarly' was associated with more extensive improvements in English writing (Chang et al., 2021), consistent with GenAI's perceived role as a levelling tool in academic language challenges.

2.3. Personality and self-esteem

Personality traits are defined as relatively stable tendencies that determine people's thoughts, emotions, and behaviours. The well-established Big Five theory of personality includes five traits: Openness to Experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (Costa & McCrae, 1992). Some studies have explored associations between personality traits and attitudes toward AI, including in 1,530 South Korean adults (Park & Woo, 2022), 259 Turkish adults (Kaya et al., 2024), and 300 UK-based adults (Schepman & Rodway, 2023). However, results regarding the associations between personality traits and attitudes to AI have been mixed. Openness to Experience did not significantly predict AI attitudes (Kaya et al., 2024). Conscientiousness was not found to predict attitudes towards AI (Kaya et al., 2024), while Schepman and Rodway (2023) found a relationship. Greitemeyer and Kastenmüller (2023) found that conscientiousness was negatively correlated with the intention to use GenAI for academic work. Kaya et al. (2024) found no association between Extroversion and either positive or negative attitudes toward AI, while Schepman and Rodway (2023) found that more introverted individuals had more positive attitudes toward AI. Kaya et al. (2024) reported that Agreeableness predicted negative attitudes toward artificial intelligence, while Schepman and Rodway (2023) found that Agreeableness was associated with forgiving attitudes toward negative aspects of AI. No relationship was observed between Neuroticism and attitudes toward AI (Kaya et al., 2024), despite the potential association between Neuroticism and the tendency to resist change (Barnett et al., 2015). Finally, higher self-esteem has been associated with both less AI use (Rodríguez-Ruiz et al., 2024) and more AI use (Chauhan & Soni, 2024). Thus, while past research has explored relationships between personality and attitudes towards–and use of–novel technology and AI, findings appear partially conflicting. Here, we sought to add to this body of research by exploring whether personality and self-esteem would predict the use of GenAI in university assignments, self-reported AI addiction, and GenAI attitudes in UK undergraduate students.

2.4. Academic behavioural confidence

Some evidence suggests that students less confident in their academic ability may be more prone to using GenAI. For example, Johnston et al. (2024) found that students more confident in their academic writing ability were less likely to report using, or considering using, GenAI for academic purposes than students with lower confidence. To the best of our knowledge, AI use and attitudes have yet to be explored in relation to the Academic Behavioural Confidence Scale (Sander & Sanders, 2006), which measures students' confidence in actions and plans related to academic study, and we sought to address this gap.

2.5. Cognitive ability: working memory

Finally, working memory is thought to play a crucial role in learning and education (Forsberg et al., 2021a, 2021b), is correlated with fluid intelligence and reasoning ability (Unsworth et al., 2014) and has been found to predict performance on various tasks, including reading comprehension, mental arithmetic, and copying from the board (Alloway & Copello, 2013). Klarin et al. (2024) explored the relationship between self-reported executive functioning and GenAI use in Swedish adolescents. They used the Behaviour Rating Inventory of Executive Functioning to assess subjective experiences of executive function, like the ability to resist a behavioural impulse (Inhibition), and the ability to hold information in mind during task completion (Working Memory). They found that adolescents who reported experiencing more executive functioning challenges perceived GenAI as more beneficial for their schoolwork. Research on the relationship between cognitive abilities and AI use appears sparse, and we sought to explore this relationship in our study. We sought to explore associations between demographic characteristics (gender, age, and mother-tongue), personality factors (the 'Big Five' Personality Factors, Self-Esteem, and Academic Behavioural Confidence), a measure of cognitive ability (working memory), and student use of –attitudes towards–GenAI. 3. Methodology.

3. Methodology

3.1. Design

In light of the objectives of this study, an exploratory sequential design, comprising both quantitative and qualitative phases, was selected. In the quantitative phase, we explored the relationship between individual factors concerning AI use, AI addiction, and attitudes towards AI in UK university students to better understand potential inequalities in GenAI use. The qualitative phase included undertaking a series of focus-group discussions to further explore students' views and experiences regarding the use of these tools. The study received ethical approval from the local Ethics Committee. The methods and all

Table 1. Participant information.

Pseudonym	Gender	Department	Major
Ashley	Female	Chemical, Materials and Biological Engineering	Material Science Engineering
Bernard	Male	East Asian Studies	Korean Studies
Eva	Female	East Asian Studies	Japanese Studies
Jack	Male	Chemical, Materials and Biological Engineering	Material Science Engineering
Charlie	Male	Chemical, Materials and Biological Engineering	Chemical Engineering
Sarah	Female	East Asian Studies	Chinese Studies
Scott	Male	East Asian Studies	Japanese Studies
Timothee	Male	Chemical, Materials and Biological Engineering	Chemical Engineering

statistical analyses were pre-registered on the Open Science Framework (OSF) (https://osf.io/83zsb). Additional and not pre-registered analyses are labelled as 'exploratory'.

3.2. Participants

In the quantitative phase, the sample was recruited from Prolific using the following criteria for our participants: (1) fluent speaker of English, (2) country of residence: The United Kingdom, (3) aged 18 or older, and (4) currently or recently graduated undergraduate student. The target sample size of 250 was decided using guidelines for stable correlational estimates (see Schönbrodt & Perugini, 2013). As such, the sampling strategy was a combination of convenience sampling and self-selection. All participants completed a survey consisting of demographic questions, questionnaires, open-ended questions related to GenAI, and a measure of working memory. Participants were provided with an informed consent form online, ensuring they understood the study's purpose and their rights as participants. At the end of the survey, they were invited to indicate their interest in taking part in a follow-up focus group discussion.

In the qualitative phase, although survey respondents were invited to express interest in follow-up discussions, no participants opted in, thereby necessitating targeted recruitment to facilitate the conduct of focus groups. We recruited the focus group participants using various channels, including targeted email invitations, as well as general email announcements distributed through university networks. The criteria for selection of the participants included: (1) undergraduate students currently studying in the UK; (2) who are familiar with GenAI and use it for personal or academic purposes, and (3) who are willing to take part in focus group discussions voluntarily. Two focus groups were conducted with four students per group, with half of the students coming from Humanities and Social Sciences and the other half from STEM (See Table 1).

3.3. Data collection and analysis procedure – quantitative approach

3.3.1. Demographics, personality, and academic confidence

All questions are available on the OSF (https://osf.io/83zsb). First, participants answered a set of demographic questions. Then, personality was measured using the Mini-IPIP scales (Donnellan et al., 2006), including Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. We measured self-esteem using the Single-Item Self-Esteem Scale (Robins et al., 2001a). We assessed academic confidence via the Academic Behavioural Confidence scale (Sander & Sanders, 2009). Participants responded to these questionnaires using a Likert scale rating. These questionnaires were chosen as they were well-suited to answer our research questions and have well-established internal reliability. We also included four attention check questions (e.g. '*Please select 'Very confident' to show that you are paying attention to this question*') to allow the exclusion of participants who did not read the questions.

3.3.2. GenAI use, addiction and attitudes

Three dependent variables measured *GenAI use*, *GenAI addiction*, and *GenAI attitudes and usage perceptions*. Gen*AI use* was assessed by a single question ('Do you use text-based GenAI tools for your course assignments?'), with the following four response options: 'Yes', 'No', 'Prefer Not to Say', and 'Other'. *AI addiction* was also assessed by a single question ('Do you agree with the following statement: I am addicted to GenAI tools when it comes to my studies'?), with the same four response options. We assessed *GenAI attitudes and usage perceptions* using a composite score of five questions related to

Table 2. Example of the questions.

Focus group discussion example questions
For what purposes do you use GenAI tools? In what domains or for what purposes?
Could you share any concerns you have about using GenAI?
What type of GenAI tool do you tend to use? Is it ChatGPT or another tool?
How useful do you find these tools?
How frequently do you use GenAI tools?
Do you feel addicted to using GenAI tools?

frequency of AI use in daily life, frequency of AI use in study activities, attitudes, comfort with usage, and usefulness for tests, using 1 to 5 Likert scale ratings. Finally, some open-ended questions further explored GenAI use and experience.

3.3.3. Working memory

We used the O-SPAN measure of working memory (Unsworth et al., 2005). Participants were presented with math problems, each followed by a number (e.g. '7') and an English letter (e.g. 'F'). They were asked to determine whether the answer to the math problem was the number presented (by clicking 'TRUE' or 'FALSE'). Then, at the end of each series of math problems, they were asked to recall the letters by selecting letters in serial order from a matrix of 12 possible letters. The O-Span score is the sum of all perfectly recalled sets. For example, if someone correctly recalled 4 letters in a set size of 4, and 3 letters in a set size of 5, their O-Span score would be 4, as the scores for each set would be 4 and 0. Participants with less than 85% accuracy on the math problems were excluded from all analyses using the O-Span measure.

3.4. Data collection and analysis procedure – qualitative approach

We carried out focus group discussions with a more targeted and smaller group to better understand the phenomenon (Creswell & Clark, 2017) but also to give them an opportunity to share their experiences of using GenAI. The focus group guide was created based on the quantitative findings, with survey results highlighting key areas for further exploration. These patterns helped shape specific discussion prompts that asked participants to explain their decision-making, perceived risks, and ways context influences GenAI use. Table 2 presents examples of the questions used to guide the focus group discussions.

The focus groups were recorded for transcription upon receiving the participants' permission. Pseudonyms were assigned to each participant to maintain confidentiality. The participants were asked to respect the confidentiality of their fellow participants and not to disclose any details of the discussions to people outside of the focus group. The participants were also provided with detailed information sheets and signed consent forms before data collection. As the topic of the focus groups was GenAI, the participants were made aware that they did not need to respond to questions that they would rather not answer.

The transcripts of the focus groups were uploaded into a software called Dedoose (https://dedoose.com/) to start the thematic data analysis process. The transcripts were initially read multiple times to start getting a sense of the data. After familiarising with the data, the transcripts were coded inductively, meaning that no predetermined codes or themes were applied. An iterative coding process was used to identify recurring patterns, such as stigma, fear of misuse, and policy ambiguity, which helped clarify and give context to the quantitative trends. The codes that shared and portrayed common features were organised into three respective themes: *views on GenAI, affordances and the reasons for the use, ethical implications and concerns*. The identified themes were thoroughly examined to ensure that the data were presented cohesively. Following this, the most pertinent quotes were highlighted and selected to depict the participants' views on GenAI and their experiences of using the tools, as elucidated in the subsequent section.

4. Results

4.1. Quantitative approach

4.1.1. Participant demographics

Overall, 262 participants took part in the study. Following our pre-registered exclusion criteria, we excluded and replaced 12 participants who failed one or both attention check items for a final sample

Table 3. Frequency of interaction with specific GenAI tools.

How frequently do you interact with the following GenAI tools for study purposes?	Not sure	Rarely or never	About once a month	About once a week	Daily
Text-based GenAI tools	0.8%	24.8%	22.8%	34.8%	16.8%
Image generation using AI	4.8%	76.8%	9.6%	7.2%	1.6%
Video generation AI tools	8.0%	82.4%	5.2%	4.0%	0.4%
Voice assistant	1.2%	53.2%	10.8%	19.2%	15.6%
AI-enabled productivity tools	4.0%	63.2%	16.8%	11.6%	4.4%
Coding or designing AI tools	6.8%	71.6%	10.0%	8.8%	2.8%

of 250 participants. The average age of the final sample was 26.4 years ($SD = 8.8$). The sample included 133 female (53.2%), 115 male (46.0%), and two non-binary (0.8%) participants. Participants were distributed across the years of undergraduate study (in the academic year before the summer of data collection) as follows: 1st year = 49, 2nd year = 80, 3rd year = 72, 4th year = 40, and 'other'; specified as either 5th or 6th year = 9 participants. Twenty-five participants reported that their mother-tongue or first language was not English, while 225 participants reported that it was. 164 of the participants reported their nationality as either 'British' or 'UK', 26 as 'English', 6 as 'Scottish', 1 as 'Welsh' and 1 as 'Northern Irish'. The second largest nationality group was Nigerian (N = 26), while all additional nationalities had between 1 - 4 participants (Finnish, American, Chinese, Dutch, German, Indian, Irish, Italian, Malaysian, Korean, Lithuanian, Pakistani, Polish, Portuguese, Romanian, and Swedish). The following Ethnicities were reported: Asian/Asian British = 34, Black/African/Caribbean/Black British = 40, Chinese = 7, Mixed/Multiple ethnic groups = 10, White = 156, Other = 3. We present participants' self-reported frequency of use of specific GenAI tools for study purposes in Table 3. Text-based GenAI tools were used daily by 16.8% of respondents and about once a week by 34.8% of respondents. Voice assistants were used daily by 15.6% of respondents and about once a week by 19.2% (see Table 3).

4.1.2. Demographics factors and GenAI use, addiction, and attitudes

We explored the roles of age, gender, and having English as one's mother tongue or first language on self-reported GenAI use and 'addiction' using Bayesian Logistic Regression. Our hierarchical Bayesian logistic regression models estimated the effect of gender (male vs. female), mother tongue (English or not English), and age (coded as a continuous factor) on self-reported AI use and addiction (the parameter η *(eta)* in our model), accounting for the binary distribution of the data ('Yes' or 'No'), using a Bernoulli distribution. We used a normally distributed prior for η specified by set prior ('normal(0,5)', using recommendations by Bürkner (2017). The dependent variable was Yes versus No responses (coded as 1 or 0) for each participant. Such multilevel models yield not only the mean but also a measure of the uncertainty of each parameter (the Bayesian Credible Interval), which conveys the range of values in which we can be certain, with a specified probability (here, 95%), that the 'true' estimate of the parameter can be found within the population (Kruschke & Liddell, 2018). Thus, when interpreting the analyses outlined below, Bayesian credible intervals that do not straddle 0 indicate that the specified parameter had a credible effect on the outcome variable. In contrast, intervals that do staddle 0 indicate no effect. In other words, a 'credible' difference (e.g. between female and male participants) is conceptually similar to a 'statistically significant result' using a frequentist approach, while 'no credible differences' are similar to results that are not statistically significant.

4.1.3. GenAI use for course assignments

First, we explored associations between gender, English as mother tongue, and age on self-reported AI use, using Hierarchical Bayesian logistic regression. 224 participants were included, as 24 were excluded from these analyses for not replying either 'yes' or 'no', and 2 non-binary participants were excluded, as this group was too small to produce reliable estimates. This analysis detected credible evidence for an age effect, with less self-reported AI use with increasing age (η=-0.04; SE = 0.02, 95% CI[0.00, 0.07]). Credible differences for gender (η=-0.14; SE = 0.28, 95% CI[−0.68, 0.41], $d = 0.046$) and mother-tongue (η=-0.11; SE = 0.45, 95% CI[−1.00, 0.77], $d = 0.009$) were not detected. We report the frequencies of GenAI use by gender, age, and mother-tongue in Table 4.

Table 4. GenAI Use, addiction and attitude by gender, age, and mother-tongue.

	AI use*	AI addiction*	AI attitudes composite score	AI familiarity
Gender				
Female (N = 133)	47.2%	9.0%	15.8 (4.8)	4.8 (1.6)
Male (N = 115)	49.5%	11.6%	17.1 (4.9)	5.3 (1.5)
Non binary (N = 2)	50.0%	0%	10.5 (2.1)	5.0 (2.8)
Age groups				
18–25 years (N = 155)	52.1%	12.4%	16.8 (4.7)	5.3 (1.4)
26 and older (N = 95)	41.7%	6.4%	15.6 (4.7)	4.7 (1.7)
Mother tongue				
Yes (N = 225)	48.3%	9.9%	16.4 (4.7)	5.1 (1.5)
No (N = 25)	47.8%	12.0%	16.0 (6.4)	4.8 (2.0)

Note: *Percentages of participants who chose either 'yes' or 'no' (excluding participants who chose the other or prefer not to say response options for the use or addiction questions, respectively). Values in Parenthesis represent Standard Deviations.

4.1.4. GenAI addiction

Our analysis on self-reported GenAI addiction included 245 participants (we excluded three participants for not replying either 'yes' or 'no', and two non-binary participants). We detected credible evidence for an age effect, with less self-reported GenAI addiction with increasing age ($\eta = 0.09$; SE = 0.04, 95% CI[0.02, 0.17]), while credible differences for gender ($\eta = -0.38$; SE = 0.43, 95% CI[−1.22, 0.47], $d = 0.085$) and mother-tongue ($\eta = -0.02$; SE = 0.70, 95% CI[−1.52, 1.22], $d = 0.066$) were not detected. We report the frequencies of GenAI addiction by gender, age, and mother-tongue in Table 4.

4.1.5. GenAI attitudes and usage perceptions

Next, we used Bayesian linear regression to explore GenAI attitudes and usage perceptions, quantified using a composite score of five survey questions, using a Likert scale with five response options ($\alpha = 0.88$). These items included *frequency of use in daily life*, *frequency of use in study activities*, *attitudes*, *comfort with usage*, and *usefulness for tests*. The analysis included 248 participants (again, excluding the two non-binary participants). We detected credible evidence for less positive attitudes to GenAI in older participants ($\eta = -0.09$; SE = 0.03, 95% CI[−0.16, −0.02]) and that male participants had more positive attitudes and usage perceptions ($\eta = 1.43$; SE = 0.64, 95% CI[0.19, 2.71], $d = 0.27$ see Table 4 for mean values). However, mother-tongue had no credible differences ($\eta = 0.74$; SE = 1.01, 95% CI[−1.30, 2.68], $d = 0.10$).

4.1.6. GenAI familiarity

Finally, in an exploratory Bayesian linear regression analysis, we explored the associations between demographics variables and familiarity ratings, in which participants rated their familiarity with GenAI on a scale from 1 to 7. This analysis included 248 participants (excluding the two non-binary participants). For this GenAI familiarity measure, we also detected credible evidence that younger participants ($\eta = -0.04$; SE = 0.01, 95% CI[−0.07, −0.02]) and male participants ($\eta = 0.57$; SE = 0.19, 95% CI[0.19, 0.95], $d = 0.33$) both reported higher familiarity. However, we found no relationship between mother-tongue and GenAI familiarity ($\eta = 0.47$; SE = 0.32, 95% CI[−0.16, 1.09], $d = 0.22$).

4.1.7. Personality and GenAI use, addiction, and attitudes

The analyses below explored associations between 1) Big Five Personality Factors (Mini-IPIP scales; Donnellan et al., 2006), 2) Academic Behavioural Confidence (Sander & Sanders, 2009), and 3) Self-Esteem (Single-Item Self-Esteem Scale; Robins et al., 2001a). In our sample, Cronbach's alpha for the Big Five Personality factors were as follows (Openness: $\alpha = 0.73$, Conscientiousness: $\alpha = 0.75$, Extraversion: $\alpha = 0.81$, Agreeableness: $\alpha = 0.77$, Neuroticism: $\alpha = 0.68$), and Cronbach's alpha for the Academic Behavioural Confidence scale was $\alpha = 0.94$. The validity of the single-item Self-Esteem measure has been demonstrated in adults (see Robins et al., 2001b).

4.1.8. GenAI use for course assignments

First, using Hierarchical Bayesian logistic regression, we explored the associations between personality traits, academic confidence, self-esteem and self-reported GenAI use. This analysis detected credible evidence for an effect of self-esteem, as participants with higher self-esteem were more likely to report using GenAI for their course assignments (η=−0.34; SE = 0.16, 95% CI[−0.65, −0.03]). However, none of the Big Five personality traits were credibly associated with GenAI use (ηs ranged from −0.18 to 0.10, all credible intervals straddling zero), and the academic confidence composite score was not credibly associated with GenAI usage (η = 0.02; SE = 0.01, 95% CI[−0.01, 0.05]). In an exploratory analysis, we tested the four Academic Behavioural confidence subscales (Confidence in *Grades*, *Verbalising*, *Studying*, and *Attendance*). We found no credible relationships between these subscales and GenAI use (ηs ranged from −0.03 to 0.10, all CIs straddling zero).

4.1.9. GenAI addiction

None of the personality factors, self-esteem, or academic confidence were credibly associated with GenAI addiction use (ηs ranged from −0.24 to 0.34, all credible intervals straddling zero). In an exploratory analysis, we tested the four Academic Behavioural confidence subscales (Confidence in *Grades*, *Verbalising*, *Studying*, and *Attendance*). We found no credible relationships between any of these subscales and GenAI addiction (ηs ranged from −0.05 to 0.06, all CIs straddling zero).

4.1.10. GenAI attitudes and usage perceptions

This analysis detected credible evidence that higher self-esteem was associated with more positive attitudes to GenAI (η = 0.74; SE = 0.34, 95% CI[0.11, 1.43]). However, none of the Big Five personality traits was credibly associated with AI use (ηs ranged from −0.24 to 0.26, all credible intervals straddling zero), and the academic confidence composite score was not credibly associated with AI attitudes (η = 0.04; SE = 0.03, 95% CI[−0.03, 0.10]. An exploratory analysis found no credible relationships between any of these Academic Behavioural confidence subscales (Confidence in *Grades*, *Verbalising*, *Studying*, and *Attendance*) and GenAI attitudes and usage perceptions (ηs ranged from −0.11 to 0.20, all CIs straddling zero).

4.1.11. GenAI familiarity

An exploratory analysis suggested a positive association between self-esteem and GenAI familiarity (η = 0.22; SE = 0.11, 95% CI[0.01, 0.44]), and an association between Openness and GenAI familiarity (η = 0.31; SE = 0.13, 95% CI[0.05, 0.57]). No associations were found between familiarity and the other personality factors or the academic confidence composite score. However, higher confidence on the Grades subscale was associated with higher levels of GenAI familiarity (η = 0.11; SE = 0.03, 95% CI[0.05, 0.18]). No associations were found for the other Academic Confidence subscales; Verbalising (η = 0.04; SE = 0.03, 95% CI[−0.01, 0.09]), Studying (η=−0.08; SE = 0.04, 95% CI[−0.17, 0.00]), and Attendance (η=−0.04; SE = 0.04, 95% CI[−0.12, 0.05]).

4.2. Working memory and GenAI use, addiction, and attitudes

The analyses below explored associations between working memory (measured using the O-Span task; Unsworth et al., 2005) and GenAI use, addiction, and attitudes. We excluded nine participants who performed less than 85% of the maths part of the task from these analyses.

4.2.1. GenAI use for course assignments

First, we used Hierarchical Bayesian logistic regression to explore the associations between working memory span and self-reported AI use. 226 participants responded either yes or no for this measure, resulting in a sample of 217 for this analysis, following the math exclusions. There was no association between working memory span and self-reported GenAI use (η = 0.00; SE = 0.01, 95% CI[−0.01, 0.02]).

4.2.2. GenAI addiction

We performed a similar analysis using self-reported AI addiction as the outcome measure. 247 participants responded either yes or no for this measure, resulting in a sample of 236 for this analysis, following the math exclusions. We did not find an association between working memory span and self-reported GenAI addiction (η = 0.01; SE = 0.01, 95% CI[−0.02, 0.03]).

Table 5. Categorised responses to open-ended questions about GenAI use.

Familiarity	Slightly familiar and rarely used 28.4%	Very familiar and frequently used 22.8%	Moderately familiar and occasionally used 16.8%	Extremely familiar and always used 10.4%	Not familiar and never used 7.6%
Purpose of Engagement	Writing/ brainstorming 39.6%	Research support 29.6%	Assignment/study/ university work/ exams 22.8%	Hobby 15.6%	Administrative support 5.2%
Motivation	Efficiency and timesaving 42.8%	Finding information 15.2%	Study purposes 12.4%	Writing purposes 6.8%	Getting feedback 4.8%
Use for Study Purposes	Understan- ding content better and preparing for exams 42%	To write better 30.4%	No/Not relevant 28.4%	Finding information and research 10.8%	Problem solving 3.6%
Addiction	No/Not applicable 89.2%	Addicted due to study purposes 8.8%	Addicted due to efficiency 1.2%	Turned into a habit 0.8%	Addicted due to its availability 0.8%

4.2.3. GenAI attitudes and usage perceptions

Using Bayesian linear regression, we explored the association between working memory span and attitudes towards GenAI, in 239 participants. There was no association between working memory span and GenAI attitudes and usage perceptions ($\eta = 0.03$; SE = 0.02, 95% CI[−0.01, 0.06]).

4.2.4. GenAI familiarity

In an exploratory Bayesian linear regression, we found that participants with higher working memory spans reported higher familiarity rates with GenAI ($\eta = 0.01$; SE = 0.01, 95% CI[0.0, 0.03]).

4.3. GenAI use: open-ended survey responses

Participants answered five open-ended questions about their GenAI use. We coded these responses into categories and reported the frequencies in Table 5. Students reported a wide range of purposes for using GenAI. The most popular responses included using it for *Writing or Brainstorming* (39.6%) and *Research support* (29.6%). *Efficiency and timesaving* were cited as key motivators (42.8% of respondents), and other responses included *Finding information* (15.2%) and *Getting feedback* (4.8%). In the context of study purposes specifically, 42% of students reported using GenAI to *understand content better and to prepare for exams*, and 30.4% reported using GenAI to *write better.*

4.4. Qualitative approach

4.4.1. Views on GenAI

The first major theme that emerged from our analysis was the students' views on GenAI. The students generally expressed positive views on GenAI and highlighted its potential uses and practical benefits. They shared their insights into these tools' various capabilities and how they can be used to improve efficiency, enhance their work, and offer new possibilities in their respective majors. For instance, one of the students, Bernard, shared that:

> I would say that AI is quite good at simplifying a lot of very complex terms and theories; it is really good for explaining to you without the fear of judgment, maybe from professors or anything.

As Bernard observed, GenAI fosters a non-judgmental educational environment where individuals may pose any questions without the concern of judgment, an issue that often accompanies interactions with academic instructors. With the integration of GenAI, students are able to explore subject matter and seek clarification regarding any uncertainties they may possess comfortably. Similarly, Jack also emphasised the capability of such tools to deliver improved explanations by stating that:

> I think a lot of the time, it's really good for explanations and definitions that often Google or just a normal search can't really give you.

Others agreed with this point as they mentioned that the tools can be 'quite helpful with summarising the general idea of a question' (Ashley) and that 'it can help speed up the processes' (Timothee).

Most participants named ChatGPT as their preferred type of GenAI tool, noting it as their top choice among other available options.

> I think it's quite good on the whole but it's not fully accurate a lot of the time. So, it's more of a starting point for me if I can get a general idea of what it's trying to tell me … That's probably the main one I use. (Jack)

Similarly, others mentioned that ChatGPT served as their starting point simply because it is widely accessible, well-known, and effective at providing general explanations. At the same time, the students shared that they tend to use ChatGPT on various occasions, depending on the specific assignment or their needs. Thus, the frequency of their usage varied as some reported using the tool: 'during exam period' (Eva), 'depending on how many essays I've got' (Scott), and 'it's probably every day and then when revising for exams' (Jack).

4.5. Affordances and the reasons for the use

As noted in the previous section, most students viewed GenAI as a valuable tool, highlighting its numerous affordances and capabilities, particularly when it comes to educational purposes. Most participants shared that they utilise GenAI and ChatGPT in particular for independent learning. This includes finding definitions of content-specific terms or looking up the meaning of the words during the lectures. As Jack noted, 'A lot of time in lectures they say words that you might not know … so it's easy to get the definition really quickly as they are speaking'. Others noted that they prefer to use GenAI to search for the needed information to prepare for a lecture or exam. Ashley remarked,

> 'It's the university's policy not to give solutions in my year. and so, searching up answers to get them fast instead of booking a meeting with one of the course leaders is just a lot more faster and just efficient'.

GenAI's efficiency and ability to provide quick answers were highly valued by most of the students, especially when they felt stuck. Jack expressed that:

> My lecturers don't give out answers to questions that they set so they expect you to go away and then use lecture notes to figure out the answers. But sometimes you just get quite stuck, and although they're quite happy to answer any email that takes time. So, a lot of the time it's just easier to get an AI answer to help you on the right track.

Additionally, several participants reported using ChatGPT specifically to help summarise articles. They mentioned that long and academic articles can be 'overwhelming', and that GenAI simplifies the process of 'summarising key points' and providing 'more understandable explanations'. Other forms of self-directed learning noted included locating relevant information and transcribing lecture notes.

One of the most mentioned affordances of GenAI among students was assistance with writing. Some highlighted that they tend to utilise ChatGPT as their writing assistant by prompting it to give suggestions on how to improve an essay. For instance, Scott shared that:

> I asked ChatGPT how I can make my work more academic, and it reworded everything. I would never just copy and paste it but highlighted some areas that I could use in my analysis more and ended up getting 90 in that essay. It was super helpful for me to get that critique from ChatGPT as it was almost as if it was a person reading it and highlighting my mistakes, but obviously, it's not always accurate.

Others also noted using ChatGPT to receive feedback on their writing as 'it's able to pick up on so many grammatical errors and not only highlight them but it can also explain them'. Checking for grammar mistakes was also mentioned among participants majoring in a foreign language or learning a new language. This group of participants noted ChatGPT's usefulness in providing translations, checking spelling, and simplifying the language of the texts to match their level. Some participants remarked that GenAI boosts their productivity and helps with procrastination. For instance, Ashley shared that:

> I only really use it to cut down tasks and make it a bit easier to understand initially. I have got ADHD, and so it helps me from procrastinating if the test seems easier to approach like that.

Other forms of assistance mentioned by participants included reordering references alphabetically, checking for spelling mistakes, and using the tool as a search engine.

4.6. Ethical implications and concerns

While the students' views regarding GenAI were generally positive, and they highlighted its numerous affordances, they still voiced their concerns and demonstrated their awareness of its ethical implications. Almost all of the students' concerns were regarding the use of ChatGPT for educational purposes. For instance, Bernard shared that:

> It's quite hard to paraphrase what ChatGPT says, especially when it's already simplifying a complex term or definition. I think that's quite difficult to put into my own words. So, I'm just scared that it flags up in the system and I get penalised for it.

Concerns about the similarity rate and risks of plagiarism were particularly pronounced among students, making some feel afraid to use the tools. Others were afraid to use the tools in academic work due to strict faculty policies. As Jack explained:

> We have a form that we fill out to say whenever we have used AI. Just for any purpose, even if it's searching, they want you to list all of it. So, it's quite in-depth of how they want you to display how you have used it. So sometimes it puts you off using it.

The students mentioned that there is a stigma attached to using GenAI in academia, as they are frequently discouraged from using these tools or asked to report how and when they have used them. According to Sarah:

> I think my concern is such a big stigma about AI when it comes to implementing education to the point where I'm really scared to use it sometimes, especially when assisting in writing essays and it's really unfortunate because it's really useful.

Another student, Amelia, emphasised this point by stating that her course prohibits the use of GenAI and added that: 'it would become better in academia once that stigmatism kind of goes'. Students' worries and fears about using GenAI tools are understandable, considering the regulations universities set. They emphasised the need for a supportive and guiding approach. Instead of discouraging use, it's crucial to offer clear guidelines for responsible interaction with these tools. By providing guidance and involving students' perspectives, universities can better prepare them to adapt to rapidly evolving technology while maintaining ethical standards. As Timothee said, learning to 'use AI to help us but not to do it for us' is essential.

5. Discussion

In this sample of 250 UK-based undergraduates, we found that younger students were more likely to use, be addicted to, and have more positive attitudes towards and familiarity with GenAI. Moreover, while self-reported usage levels (i.e. the proportion of students who reported using GenAI for their coursework) were similar between female and male students, male students reported more positive attitudes towards GenAI and higher degrees of familiarity with GenAI. This interesting pattern of results suggests that gender differences in non-academic GenAI use may not generalise to academic GenAI use. However, this potential pattern, and potential intersectional interactions with other factors, such as age, require more fine-grained exploration in future studies. No associations were found between participants' mother-tongue or first language (English or Not English) and any GenAI outcomes variables. There were no associations between Big Five personality factors and GenAI use or addiction, but participants who scored higher on the trait of Openness to Experience reported higher GenAI familiarity. Interestingly, participants with higher self-esteem were more likely to report using GenAI for course assignments. Participants with more confidence in their ability to achieve good grades (measured using the *Grades* subscale of the Academic Behavioural Confidence Scale) reported higher GenAI familiarity, but no associations were found for the remaining subscales (*Verbalising*, *Studying*, and *Attendance*). Finally, while working memory span was not associated with differences in GenAI use or addiction, participants with higher working memory spans reported higher familiarity with GenAI.

The exploration of students' views on GenAI tools uncovered their positive attitude towards them and, at the same time, their concerns associated with their use. It was seen that students viewed the tools in a positive light as they listed their numerous capabilities and shared how they can be utilised in practice. The students highly valued GenAI's ability to help them in their studies, specifically for independent learning and writing support. It was revealed that the students benefited from GenAI's immediate and on-demand support. Moreover, the students reported finding these tools to be efficient in locating relevant information, transcribing lecture notes, and summarising articles (Berg, 2023). When it comes to writing assistance, students shared that they utilise GenAI to receive feedback on how they can improve their writing. They prompt the tools to give them suggestions, check their work for grammar and spelling mistakes, and help them understand how to improve their writing.

On another note, while students were positive about GenAI, they also expressed their concerns regarding the usage of these tools. One of the main concerns among students was ethics and plagiarism as they feared that using GenAI could potentially put their academic integrity at risk. Students also expressed that they were afraid to use the tools due to the stigma associated with GenAI in academia (see Giray, 2024) and because the university discourages the use of such tools. However, they expressed that they utilise GenAI not as a tool for cheating but instead as a resource that supports and enhances their learning. Thus, students highlighted the importance of establishing clear guidelines for using GenAI in academic settings, enabling them to utilise the tools ethically and responsibly.

6. Limitations

This study has several limitations that should be acknowledged. First, recruiting via Prolific enables a large sample and reduces social desirability bias because participants are truly anonymous; however, we have limited knowledge about their specific educational contexts. Therefore, while the sample provides a broad overview of students across the UK, we cannot confirm the institutional policies and guidelines communicated to them, nor can we systematically examine their influence. Additionally, the cross-sectional design captures attitudes at a single point in time, rather than tracking how usage and attitudes evolve. Future research could use longitudinal designs to explore how evolving institutional GenAI policies over time impact students' perceptions and learning strategies. Second, the quantitative analyses are limited to binary or Likert scale responses, which reduce potentially complex phenomena into a specific, pre-determined response option. For example, the binary 'GenAI coursework use' measure does not separate between students who may have used GenAI to support a small part of their learning process when encouraged to do so by their instructors, from students who rely on GenAI consistently for most or all aspects of their coursework. Third, the operationalisation of 'addiction' in this study also has several limitations. Addiction is a clinical construct, but may also be used in a more 'humorous' everyday way, i.e. implying something we rely on or use more than we would like, but without any clinical implications. We did not guide participants on how to interpret this term, and it is therefore unclear how participants interpreted this question. As such, future research is needed to distinguish the various potential meanings of this term.

7. Conclusion

In a sample of 250 UK undergraduates, we found that younger students were more likely to use–and report 'being addicted to'–GenAI for their coursework. While there were no gender differences in GenAI use for coursework, male students reported higher degrees of familiarity with GenAI. Participants' mother-tongue was not associated with any of the GenAI variables in our sample. However, our sample included mainly participants who reported that English was their first language. Interestingly, participants with higher self-esteem were more likely to report using GenAI in their coursework. Next, students more familiar with GenAI reported being more confident in their ability to achieve high grades. Working memory span was not associated with differences in GenAI use, addiction, or attitudes, but participants with higher working memory spans reported higher degrees of GenAI familiarity. In contrast to some previous studies, we did not find any associations between the big five personality traits and GenAI use, apart from a positive relationship between Openness to Experience and GenAI Familiarity (Schepman & Rodway, 2023).

Given the correlational nature of our study, these findings are open to multiple interpretations. For example, students with higher self-esteem may feel more assured in their ability to use GenAI without negative consequences. Similarly, students who are more confident in their ability to achieve good grades may also be more confident in their ability to use new technologies. However, none of the other facets of academic confidence–apart from the grade facet–were associated with increased GenAI familiarity, suggesting that this relationship was not driven by general academic confidence but related explicitly to confidence around assessments. Alternatively, students who are more familiar with GenAI may feel more confident in their ability to achieve good grades because they perceive GenAI as a helpful tool. Future research could explore confidence in grades before and after increasing students' GenAI familiarity to better understand the potential causal relationships. The theoretical mechanisms underpinning the observed association between working memory ability and self-reported GenAI familiarity in our study also warrants further exploration. Klarin et al. (2024) found that adolescents who reported more subjective executive functioning challenges perceived GenAI as more beneficial for their schoolwork. People with lower working memory capacity appear more likely to overestimate their cognitive abilities than those with higher working memory capacity. Higher actual ability may be associated with more subjective awareness of cognitive challenges, which may predict increased interest in GenAI. However, in our study, working memory capacity was only related to self-reported familiarity with GenAI, not the use of GenAI for coursework, and further exploration is needed. Future research may explore whether potential correlations between differences in working memory ability and University degree choices may partially explain this association. For example, individual differences in working memory capacity have been found to predict mathematics achievement (see Spiegel et al., 2021, for a meta-analysis), which may potentially contribute to degree choices and exposure to GenAI.

The key outcomes of study one suggests that various factors like age, and self-esteem may predict the use of GenAI in academic coursework. While reported usage for academic coursework was similar between male and female participants, male students reported more positive attitudes towards GenAI and higher degrees of familiarity with GenAI. Moreover, higher GenAI familiarity was also reported by participants who scored higher on the trait of Openness to Experience, participants with more confidence in their ability to achieve good grades, and those with higher working memory span, while overall self-reported GenAI use for coursework did not differ with these factors.

These findings suggest that while male and female students and students with higher and lower working memory ability, trait personality Openness, and confidence in their ability to achieve good grades–may be equally likely to report using GenAI for their coursework, there may be differences in the depth and range of their GenAI familiarity, which could potentially influence the efficiency of their GenAI assisted learning. Ensuring that all students have equal access to and familiarity with potentially useful learning tools seems important as GenAI keeps developing at a rapid pace. Relatedly, some research suggests that GenAI may widen the learning gap for students with different baseline abilities. For example, Prather et al. (2024) explored the efficiency of GenAI in beginner programmers. Their results suggested that GenAI was more helpful for students who struggled less, while for those students who struggled more with the task, GenAI appeared less helpful. Further exploration of situations in which GenAI is helpful for learning, depending on students' baseline abilities and background knowledge, in addition to improved understanding of factors that may encourage or discourage GenAI use, may inform practice going forward.

Focus group discussions revealed students' positive perceptions of GenAI, while also highlighting their nuanced perspectives that encompass both enthusiasm and concern. Evidently, students are acquainted with these tools and employ them for academic and learning activities. They described various methods of utilising GenAI and recognised it as a valuable resource that can facilitate assistance and promote autonomous learning. Despite this, students also expressed concerns regarding ethical considerations, particularly in relation to the university's policies and prevailing stigmas within academia. Some students expressed apprehensions about using GenAI due to the potential consequences of misuse. This hesitation may originate from uncertainty and the absence of clear guidelines delineating appropriate and inappropriate use. Prior research indicates that students experience stress related to ambiguity about the extent of permissible use of GenAI (Malmström et al., 2023). Echoing Biggs (2011) account of learning, it is indicative that when understanding of the acceptable practices and institutional guidelines are unclear or inconsistent, students are less likely to use GenAI in meaningful ways. Therefore, based on the findings of our study, we propose several implications for higher education institutions (HEIs) concerning the integration and application of GenAI. Firstly, HEIs should clearly articulate their stance on GenAI usage to enhance understanding and prevent confusion among students. Considering the diverse disciplines and varied applications of GenAI, a responsible approach is advised. Institutions should communicate distinctions between approved and prohibited uses, such as noting that while generating entire essays with GenAI may compromise learning outcomes and academic integrity, employing GenAI for practice problems such as brainstorming and idea generation or translation exercises may be permissible. Secondly, integrating GenAI literacy into the curricula of HEIs is essential, enabling students to comprehend its benefits and limitations and to engage with these tools ethically and responsibly, ensuring their practices do not harm society. Adoption of critical pedagogy theory and praxis in teaching and learning processes can facilitate this integration (Klyshbekova et al., 2026). For example, educators can prompt students to understand, question and evaluate AI-generated information and distinguish between reliable and unreliable sources, thereby strengthening their critical thinking skills. Alternatively GenAI can be employed to stimulate students' creativity by producing a wide range of different and unpredictable ideas and prompts (Chan & Hu, 2023). Pedagogical approaches should promote discussion-based, experiential and situated forms of learning. Finally, centering students' and educators' voices is crucial for guiding future policy decisions and ensuring institutional responsiveness. Collectively, these recommendations aim to mitigate potential inequalities in academic achievement and to alleviate stress and stigma associated with GenAI utilisation.

Ethical approval

Ethical approval for this study was obtained from The University of Sheffield School of Psychology Institutional Board.

Patient consent statement

Informed consent was obtained from all participants before their involvement in the study.

Permission to reproduce material from other sources

No third-party materials were used, therefore, permission was not necessary.

Clinical trial registration

This research did not include a clinical trial, therefore, registration was not applicable.

Authors' contributions

MK: Writing–Original draft preparation, Conceptualisation, Investigation, Methodology, Analysis, Writing, Reviewing, Editing. **AF**: Conceptualisation, Methodology, Analysis, Writing, Reviewing, Editing, Supervision.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This project was funded by a Jacobs Foundation Research Fellowship.

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Data availability statement

Preregistration (with authors' details) is available at (https://osf.io/83zsb).

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